International Journal of Open Publication and Exploration (IJOPE), ISSN: ISSN: 3006-2853
Volume 8, Issue 2, July-December, 2020, Available online at: https://ijope.com

Predictive Maintenance and Resource Optimization in Inventory Identification Tool Using ML

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ABSTRACT

Purpose: The fourth industrial revolution has given rise to a variety of concepts, one of which is maintenance planning, which is now essential to production systems since it provides a digital perspective on machine maintenance. Predictive Maintenance (PdM) is a well-known strategy that integrates all the operational techniques and protocols required to ensure machine availability and prevent a machinery-down situation. The expanding volume of data collected by sensing and intelligent machines is changing how decisions are made in the manufacturing sector.

Aim: This study examines the contributions and level of maturity of the field of machine learning algorithms for predictive maintenance.

Methods: Predicted oversights Gradient Boosting in a Random Forest, and Excessive Gradients Boosting are three tree-based classification techniques that are used to compute probabilities as the time-dependent development of event data. Woodworking machine residue useful life (RUL) can be calculated by using a combination of temporal features engineering methods and a set of classification algorithms.

Results: The Gradient Boosting model achieved accuracy, recall, and precision of 98.8%, 94.6%, and 96.8%. Our preventative care technique executed on the Big Data framework enables rapid screening of numerous machines that are connected by utilizing terabytes of log information.

Conclusion: Important information from the target forecast can be implemented into maintenance management procedures.

Keywords: Predictive Maintenance (PdM), Gradient Boosting Model, Remaining Useful Lifetime (RUL),Classification Models, Neural Networks, Comprehensive Survey, Synthesize Material, Machine Learning Techniques, Prominent Strategy, Sustainable Manufacturing.

INTRODUCTION

In the present economic situation, which is characterized by intense globalization and markets that are becoming more demanding, [1], industries are under pressure to increase the efficacy and effectiveness of their manufacturing operations in order to boost their level of competitiveness and please consumers [1, 2]. Industry 4.0, defined as connectedness, data, new technologies, inventory optimization, modifications, and controlled manufacturing, is emerging and appears to be unstoppable today.

This suggests that in order to incorporate all of the most recent innovations and therefore boost production, automation techniques must be used. In this context, cognitive automation is utilized by the Internet of Things (IoT) and Big Data technologies, along with the incorporation of AI methods and Cyber-Physical Systems (CPS) [2, 3]. This leads to the implementation of the concept of intelligent production, which in turn produces intelligent products and services. Businesses are able to tackle the demands of a much more constantly changing marketplace thanks to this creative strategy. Using prescient support, organizations might expand the existence of their business hardware, [3, 4], forestall unforeseen personal time, and lessen energy use and costs.

The practice of predictive maintenance has established itself as an acceptable approach for prolonging the life of technology by forecasting data collected by multiple sensors on machines. It has become increasingly important for industries due to the increasing complexity of the connections between different production activities in ever-larger industrial ecological systems. Figure 1, [3, 4], which shows a projection for 2022–2030, shows how this type of smart maintenance is being used globally.

Modern maintenance techniques generally differ according to the many learning models applied and the various issues that the machinery and equipment face. However, predictive maintenance requires exceptionally precise and transparent defect diagnosis and prognosis. In light of the objective of developing an intelligent manufacturing framework, [4, 5], data gathered from the equipment's sensor is used to detect, understand, and forecast equipment problems [6].

Predictive Maintenance

The goal of Predictive Maintenance (PdM), a relatively new preventative maintenance technique, is to extend equipment life and ensure sustainable operational management while simultaneously enhancing manufacturing procedure performance and efficiency. This implies, on the one hand, an overall reduction in unavailability and unneeded stops, [6, 7], accompanied by a drop in repair costs, by offering the option of intervention through failing prediction. Nowadays, companies in the manufacturing sector are using intelligent predictive maintenance strategies [7, 8]. This implementation is accomplished by calculating the remaining life of the elements that failed and by enabling remote, [7, 8], instantaneous awareness of equipment malfunctions. For the latter to operate as intended, authentication and diagnostics are necessary.

The newest type of maintenance is called preventative maintenance, and it provides the most cost-effective and environmentally friendly solutions together with the equipment's longest life and highest degree of dependability (Figure 1) [8, 9]. Proactive maintenance is the process of troubleshooting by going all the way to the source. Growing in popularity is this maintenance technique, which works extraordinarily well when combined with predictive maintenance[10].

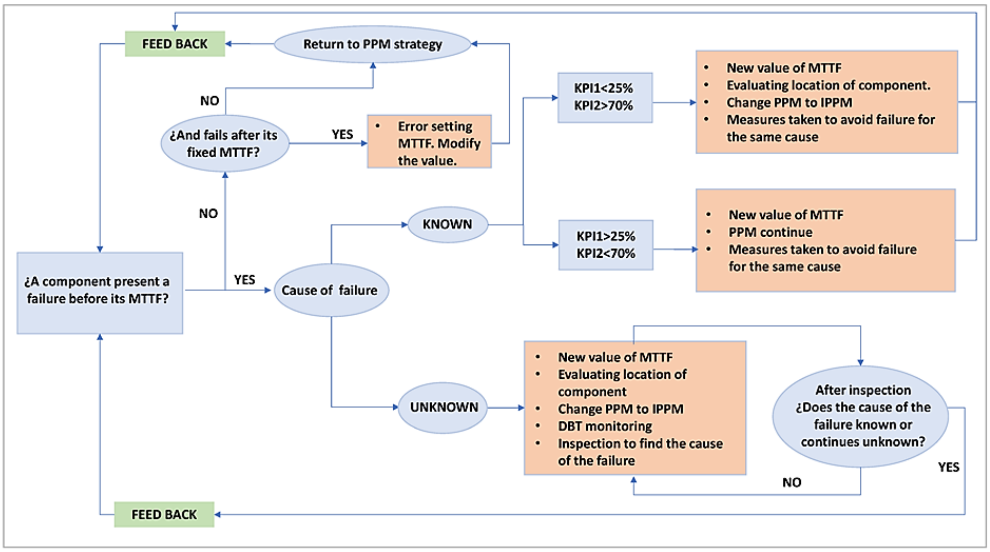

Fig. 1 A prospective failure diagram that shows the intervals of inspection and preventive maintenance

Devices and Materials for Predictive Maintenance

During the start of the modern era, the fourth industrial revolution, also called Industry 4.0, took place, and among the key components of this digital change are computational and complicated visualization tools based on the most recent innovations in technology. Manufacturing businesses have implemented them in various industrial uses, particularly in predictive maintenance, often known as maintenance 4.0 [11, 12]. The primary technological devices used in maintenance 4.0 are listed in the subsections that following.

Cyber-Physical Technologies

"Cyber-Physical Systems (CPS)" are the most recent advancements in autonomous intelligent management, tracking, sensing, and diagnosis systems as well as strategically integrated production devices and sensors [12]. They are equipped with a variety of physical and computational methods and tools that are especially well-suited to satisfying the needs of individuals. Industrial gear Because Predictive Maintenance (PdM) was designed to achieve near-zero; hidden dangers, failures, contaminants, and near-zero emergencies throughout the entirety of the manufacturing surroundings, it is capable of recognizing demeaning performances [12, 13].

Massive amounts of data have been collected for the study of Machine Learning (ML), and these data contain extremely valuable data and expertise that can be applied to decision support in various areas, especially condition-based upkeep and health surveillance, as well as enhance the overall effectiveness of the manufacturing process and the functioning of networks [13, 14]. It is now achievable to gather tremendous quantities of function and operating conditions data produced by numerous pieces of machines and harvest it for computerized failure the identification and diagnosis thanks to the most recent advancements in computer technology approaches, computerized control, [14, 15], and networked communications. The collected datasets can also be utilized to create more effective plans for preventative repair, or PdM, as it is commonly known.

Applications of Machine Learning (ML) can reduce costs while still preserving efficiency, minimizing maintenance stops, reducing machine faults, increasing spare-part life and reducing inventory, improving operator safety, boosting worker productivity, identifying repairs, increasing overall profit, and providing several additional benefits. These benefits are inextricably linked to maintenance methods [14, 15]. Furthermore, fault detection is a vital component of predictive maintenance; enterprises require the ability to detect issues at an early stage. The techniques for maintaining regulations are able to be classified into the following categories.

PdM demonstrates tremendous potential when directed by a Machine Learning (ML) method that works in the field of neural networks. The ability of machine learning to handle large amounts of data quickly is used for assessing its effectiveness [15, 16]. ML allows us to "understand" complicated procedures, assets, and data. Machine learning allows machines to directly access a big amount of example data. Agent-based methods contain code inside the internal machines engine to recognize patterns and trends, while generating alarms and breaks based on duties, products, and restrictions.

Rather than manually creating software processes with a particular combination of instructions to complete a specific task, Machine Learning (ML) examines the relationship between the information stored and the labelled produce (e.g., failures) and then establishes a model based on data to report the results in the future [16, 17]. This can identify patterns in historical occurrences and foresee or prevent failures based on insights gained from a specific break down of the fundamental causes. Cloud-based artificial intelligence systems continually acquire information from alerts. As a result, performance is improved, and machine availability increases. When compared to traditional monitoring of conditions or more traditional maintenance tactics, such as usage-based trade, an AI-based solution is anticipated to perform significantly better due to improved failure prediction.

Machine Learning (ML) algorithms are being used to solve a wide range of challenges or applications within the manufacturing industry [17]. They can be used to increase and extract predictions while reducing the difference between the sets used for training and testing. They often represent an evolution of condition-based maintenance. Open source, already prepared beta programs are readily accessible on the internet, [17, 18], which encourages usage.

However, they encounter issues with digital prototyping and collecting information. Several prominent suggestions for machine learning include unsupervised and supervised learning, inductive software development, clustering, learning through reinforcement, Bayesian networks, and decision tree learning.

Objectives of the Study

- Implement predictive maintenance solutions to decrease expenses and ensure equipment reliability.
- Use real-time monitoring systems to collect data from equipment sensors and detect abnormalities or departures from typical operating conditions.

LITRATURE REVIEW

(Morariu, C., Morariu, O., 2020) [19] Industry 4.0 (I4.0) enables connectivity, increased data volume, novel electronics, reduction in size, decrease in inventory, personalization, and controlled manufacturing. In the contemporary world, customisation as well as data accessibility are basic for delivering information that empowers dynamic cycles. One of the impediments of the course of creation is having the ability to anticipate future support necessities and apply this comprehension to different activities. In this regard, this article introduces Preventive Maintenance (PdM) & Schedule (PdMS), an approach for predicting and automatically optimizing maintenance and production schedules. Typically, these remedies are discussed independently in research.

(Zonta, T., da Costa, C. A., 2022) [20] The automation of processes in manufacturing businesses, as well as the integration of increasingly sophisticated shop floor equipment and computer control systems, have resulted in an explosion of information elements available in Manufacturers Execution System (MES). The ability of businesses to acquire value from large-scale information processes and extract usable insights is a differentiating factor in building controls that improve output and protect resources. Machine learning as well as large-scale data technology are increasing prominence and are now being used in some crucial planning and control applications. Cloud manufacturing allows you to use these developments in real time, cutting the cost for implementation and deployment. In this regard, the study presents a machine learning strategy for reality recognition and optimization in the cloud environment.

(Ayvaz, S., 2021) [21] This task made an information driven prescient safeguard support framework for creation lines underway. The framework involves AI calculations to recognize signs for potential breakdowns before they occur by dissecting information assembled continuously from IoT sensors. Subsequently, it helps with disposing of issues by illuminating administrators quite a bit early, permitting preventive measures to be executed preceding an assembling stop. In the ongoing review, the framework's adequacy was additionally assessed utilizing true assembling related IoT information. The evaluation results suggested that the planned upkeep system was effective for identifying indicators of possible failures, and it can assist avert some production distractions from happening.

(Wang, J., 2022) [22] A subset of sophisticated production known as "smart manufacturing" uses Artificial Intelligence (AI) and Computer-Integrated Manufacturing (CIM) to enable data-driven reactivity throughout the whole manufacturing cycle, from process scheduling and control and optimizing to the final product assurance for quality. This type of manufacturing is enabled by two crucial strategies: intelligent servicing forecasting and scheduling. In Industry 4.0 (I4.0)-based systems for manufacturing, all resources (e.g., machinery, robots, vehicles, materials, etc.) in a factory that is smart are represented as Cyber-Physical Systems (CPS), which are physical objects equipped with digital identification devices such as RFIDs, sensors, computational gadgets, etc.

(Nordal, H., 2021) [23] Industry 4.0 is the most recent industrial production paradigm, allowing for a new level of organization and control over every aspect of the value chain inside a product life cycle by establishing a dynamic and real-time awareness of cross-company behaviour. It is predicted to have a significant impact on the Oil and Gas (O&G) industry by modernizing present predictive maintenance and operational optimization techniques. There are various obstacles to overcome before the Industry 4.0 vision can be realized: a common reference architectural design, a business model, and robust products and services are all missing. This article creates a reference design for an intelligent management system for maintenance that adheres to Industry 4.0 objectives and requires.

(Ran, Y., Zhou, X., 2019) [24] This paper emphasizes the growing significance of maintenance methodologies for the upcoming technological age, reviews their evolution, and provides a detailed literature review on the most current developments in maintenance techniques, namely Predictive Maintenance (PdM), with a focus on architectures of systems, optimizing objectives, and strategies for optimization. In industry, any outages or unforeseen breakdowns of machinery or processes would damage or disrupt a company's essential enterprise, which might result in severe sanctions as well as irreversible reputation and economic loss. Existing traditional maintenance systems, such as Reactive Management (RM) and Preventive Maintenance (PM), have significant preventative and repair costs, insufficient or erroneous mathematical deterioration procedures, and human removal of features. The impending fourth industrial revolution necessitates a new maintenance paradigm to reduce maintenance expenses and interruptions while increasing availability and reliability. Predictive Maintenance (PdM) has been suggested as a possible remedy.

RESEARCH METHODOLOGY

Log File Analysis

Our focus was directed towards the damaged cylinder bearings piece that is causing the woodworker Rover devices to stop functioning. A minimum of five years' worth of historical data from log files have been acquired and transformed into normal output (stdout) logging files [25]. The information included in the stdout log files was collected from 14 Rover machinery: The following phrases describe how the five ES that had the broken a cylinder bearings component and the nine ES without the ball bearings (control sample) were submitted for the processing of data.

Data Science Module

Figure 2 describes the sections for data sciences. A protocol consisting of two main components—log file determination and a Machine Learning (ML) module—may be used to encapsulate our methods. The main steps of current events method include:

- Log file interpreting,
- Developed features for specified error groups,
- Developing models,
- Model evaluation.

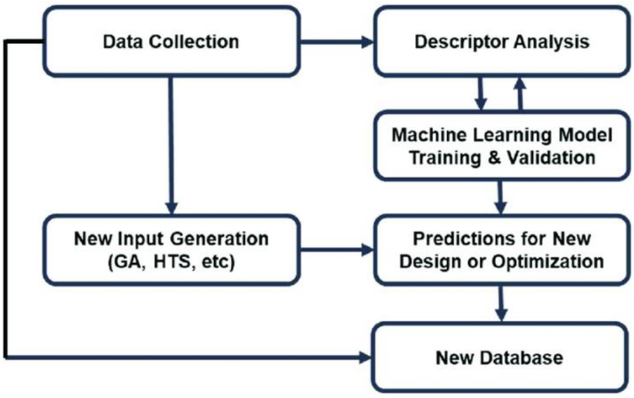

Fig. 2 Overview of the Data Processing and Science of Data modules The flowchart graphic represents the essential processes of the data mining pipelines evaluation. [26].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \ldots\ldots\ldots\ldots 1$$
$$Recall = \frac{TP}{TP+FN} \ldots\ldots 2$$
$$Precision = \frac{TP}{TP+FP} \ldots\ldots 3$$

Experimental Methods and Metrics

The data set has been divided 70-30 between testing and training teams in order to generate independent assessments of achievement. The training set (70%) was used to train the algorithm for classification and determine the best values for the hyper parameter configurations for each approach. The collection of tests was then utilized solely to evaluate the efficacy of classification [24, 25]. CV was employed on the set of training data to determine the ideal hyper parameter values. The group of experiments was subjected to a grid-search in order to determine the optimal parameter values. Table 1 shows the ranges over which the grid-search was conducted for each of the following variables: maximum dimension, learning rates, the number of trees, column sample rate, and sample rate.

Table 1A hyper parameter ranges and optimum values. [27]

Model	Hyper parameter	Optimal Values
Distribution Random Forest (DRF)	Maximizingdimension =[6,2,6,0,7] Numbering of tree =[10,25,29,30] Sampling rates=[0.5,0.9,0.2,0.9] Columns rate of sampling per tree =[0.1,0.3,0.4,0.6]	Maximizingdimension=9 Numbering of tree =29 Sampling rates =0.9 Columns rate of sampling per tree. =0.4
Gradient Boosting Machine (GBM)	Learn rates =[0.1,0.3,0.6,0.9] Maximizingdimension=[2,6,9,2] Numbering of tree =[50,120,150,250,350] Sampling rate =[0.6,0.9,0.6,0.6] Columns rate of sampling per tree =[0.6,0.2,0.3,0.9,0.3]	Learn rates =0.9 Maximizingdimension=9 Numbering of tree =140 Sampling rate =321 Columns rate of sampling per tree =0.39
Extreme gradient Boosting (XGBoost)	Learn rates =[0.2,0.6,0.2,0.9,0.3] Maximizingdimension=[5,1,6,9,4,8] Number of tree =[50,130,140,160,170,180] Sampling rates =[0.6,0.2,0.9,0.7,0.5] Columns rate of sampling per tree =[0.9,0.6,0.2,0.8,0.9,]	Learn rates =0.09 Maximizingdimension=8 Number of tree =146 Sampling rates =0.9 Columns rate of sampling per tree =0.9

EXPERIMENTAL RESULTS

Logs File Parser

In order to extract the occurrence and pre-process the data, we produced a log file with an extractor during the preliminary processing step. Collection of events recorded by numerous software programs performing on the ES equipment are designated as strong log files.

Features Engineering

In order to increase the importance of parameters in the training information set, we employed a feature engineering approach and calculated unique variables called lag characteristics using the sliding windows technique. Fixed-sized frames used for aggregate computing are called windows that are sliding.

Classifier Results

Three tree-based designs—a Distribution Randomization Forest (DRF), a Gradient-Boosting Machines (GBM), and an Extreme Gradient Boosting Machine (XGBoost)—were educated, adjusted, and put to testing throughout the classification phase. To determine the most suitable hyper value of parameters for every model, a grid-search method has been employed in Table 2.

Table 2GBM, DRF, and XGboost accuracy, recall, and precision measures have been established on data from both training and testing sets using the Cross-Validation (CV).

Model	RUL	Accuracy		Recall		Precision	
		Tanning	Testing	Tanning	Testing	Tanning	Testing
Distribution Random Forest (DRF)	40	96.2 (0.5)	98.4	98.6 (0.6)	94.6	96.5 (0.6)	100
	30	97.2 (0.1)	98.3	93.6 (0.3)	97.8	91.6 (0.3)	98.6
	20	99.2 (0.3)	94.6	94.1 (0.3)	93.1	94.6 (0.6)	96.4
Gradient Boosting Machine (GBM)	40	94..6 (0.6)	95.6	94.6 (0.3)	99.6	96.3 (0.6)	94.6
	30	98.6 (0.3)	98.3	94.9 (0.6)	94.6	94.6 (0.0)	98.6
	20	98.6 (0.4)	91.6	95.6 (0.6)	97.6	98.1 (0.2)	97.6
Extreme gradient Boosting (XGBoost)	40	94.6 (0.6)	92.6	98. (0.4)	94.6	94.6 (0.0)	92.6
	30	97.6 (0.3)	97.6	97.6 (0.3)	96.2	97.6 (0.3)	97.6
	20	97.6 (0.1)	98.6	96.1 (0.2)	97.6	93.6 (0.1)	98.6

Modelling importance of features

The GBM model's strong interpretability enables the extraction of the importance of every characteristic in order to identify the most discriminative predictions. The H2O GBM approach determines each feature's relevance based on whether it was selected separately during the following tree building stage and the extent that the squared error of the variation rose as a result.

Platform Integration for PdM Applications and Machines Down Monitor

Pyspark components were used in the machine learning distribution procedure, which was carried out on the Azure HD insights Sparking Clusters. Two master nodes, which are two slave the nodes, plus other services like distributed storage and SQL have been included within this arrangement. BIESSE manufacturing equipment is networked with each other over the internet, enabling machinery monitoring of status.

DISCUSSION

Preventative maintenance is a procedure that uses tools and condition monitoring protocols to continuously assess a structure's or piece of equipment's condition and functioning while it is continuous use. Still, the data indicates that most maintenance 4.0 apps focus on a specific piece of industrial or industrial machinery [26, 27]. It can be considered ground-breaking in the industry to create a user-friendly, multipurpose device like the one that combines various sensor types and allows in-situ PdM on a variety of machineries in in real time.

One of the challenges in putting the Industry 4.0 (Industry 4.0) strategy into practice is creating an embedded computer system that can track the health of the machine. PdM has been emphasized as a fundamental component of the Industry 4.0 architecture. By minimizing unexpected down time, its deployment enables increased productivity and decreased production costs. In order to identify event-based issues, our study concentrates on the development and application of a statistical pipeline for classifying the operational state of machine-based event data using log files [27]. PdM is implemented using unit learning techniques, which apply sophisticated analysis to newly created data streams on an interconnected unit or in the cloud. Acquiring false data to train a model under supervision is another major issue in maintaining predictions. The objective of machine learning is to collect normal state behaviour up until failure. In real-world scenarios, [27], it is not always easy to gather information about a failure event, which leads to an extremely unbalanced configuration. Nonetheless, by learning a model for machine learning with supervised training across two classes (a normal value state, an anomalous state), [28], this data is essential for creating a model that distinguishes between a normal and an inaccurate sampling.

CONCLUSION

This paper performed a comprehensive research assessment on methodologies and technologies for smart and prospective economic maintenance, encompassing the most important works on intelligent maintenance prediction. As a result, each proposed strategy might be determined to be addressing specific equipment, making comparisons with other ways more difficult. A thorough evaluation of the literature indicates that predictive maintenance is a crucial tactic for increasing effectiveness in a variety of settings, including those with aging equipment. Utilizing the globally distributed Big Data ecosystem, the suggested application case has been realized as a PdM system for building with wood, generating information-driven models for prediction based on historical log data. Every 24 hours, the PdM scheme, making use of a Big Data stream computing structure, analyses the log files and forecasts the condition of the woodworking equipment. A front-end dashboard shows the current state of failing machines, and continual monitoring of the upward trajectory for each linked machine's expected likelihood is possible. The method presented here, which was used with an industrial woodworking machinery, might also be used in other sectors where equipment logs are kept, such as those involving information technology (IT) in medical or manufacturing equipment. The results of our model evaluation showed that the classifiers had a dependable prediction capacity (up to 98.9%, 99.6%, which or 99.1% accuracy, recollection, and precision, respectfully).

Future Work

Further research could focus on expanding the suggested methodology to various components or categories of industrial machinery.

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